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UNCERTAINTIES IN LCA

Assessment and improvement of the appropriateness of an LCI data set on a system level – application to textile manufacturing

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Abstract

Purpose This paper aims at assessing the appropriateness at the system level of different Life Cycle Inventory (LCI) data sets (including default models) selected by the Life Cycle Assessment (LCA) practitioner. This means that the uncertainty measurements are applied on some specific main parameters of the LCI data set instead of measured input values. This approach aims at providing a pragmatic method to approximate and reduce the uncertainties resulting from a lack of information on a specific step.

Methods The method proposed in this paper to assess the percentage errors on appropriateness includes three main steps. First, different systems including different versions of the same process with technological or geographical changes are assessed. Second, a hierarchical cluster analysis (HCA) or a principal component analysis (PCA) is performed to identify the main variables influencing the results. Third, a multivariate analysis of variances (MANOVA) assesses the significance of the main variables on the results. An appropriate default model can be developed by setting the variables introducing high variations in results.

Results and discussion When comparing the same spinning process located in different countries, the HCA enabled us to identify the electricity mix as the main variable influencing the results. The "world average default models" has proven inappropriate to represent country specific locations. When comparing spinning technologies, the PCAs identified the electricity and the cotton input required as the main variables influencing the results and explained the variations in results due to technological changes.

The HCA performed on different yarn manufacturing procedures identified the location and the yarn thickness as the two main variables influencing the results. The MANOVA assessed the percentage marginal variance (PMV) explained by the variable *location* between 85 and 92 % for four impact categories. The MANOVA performed on different fabric manufacturing systems assessed the PMV explained by the variables *harvest*, *spinning*, and *weaving locations* above 68 % for all impact categories. The HCA and MANOVA analyses helped design an appropriate "technological average default model."

Conclusions From the identification of the main influencing variables (HCA and PCA) to the quantitative appropriateness assessment (MANOVA) and the development of appropriate default models, the method has proven effective in assisting the LCA practitioner in the modeling of textile manufacturing systems, and for other worldwide multi-step manufacturing systems.

Keywords Appropriateness error measurements · Life Cycle Assessment · Textile manufacturing

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1 Introduction

Life Cycle Assessment (LCA) data contain considerable uncertainties of various sources. Many authors introduced methods to measure parameter uncertainty and how it

propagates to the assessment results (Chevalier and Téno 1996; Benetto et al. 2008; Ciroth et al. 2004; Heijungs et al. 2005; Imbeault-Tétreault et al. 2013).

The most current practice to propagate input parameter uncertainty to LCA impact scores is a probabilistic method called Monte Carlo simulation (Lloyd and Ries 2008). These uncertainty measurements methods were applied on observed and/or measured inputs (Weidema and Wesnaes 1996; Maurice et al. 2000; May and Brennan 2003; Sonnemann et al. 2003; Bojaca and Schrevens 2010). Those measurements on observed input values require a good knowledge and traceability of the process modeled.

With the launching of large-scale LCA projects such as the environmental labeling on consumer products, more and more LCA practitioners face time constraints. And for worldwide multistep manufacturing systems, the data collection process is tenuous, and the lack of traceability precludes on-site measurements. To avoid data gaps, a common timesaving practice among the LCA practitioners consists in replacing the required data with a default model or unrepresentative data. Unfortunately, the use of inappropriate data introduces high uncertainties.

The method introduced in this paper aims at reducing the uncertainties resulting from a lack of information on a specific step. In order to gain insight of the complex relationship between the input data and the Life Cycle Impact Assessment (LCIA) results, we have favored in this paper the use of well-known statistical methods such as principal component analysis (PCA), hierarchical clustering analysis (HCA), and multivariate analysis of variances (MANOVA) combined with visualization techniques. These tools present the advantage of handling non-numerical data. The method necessitates two main analyses:

– Identification of the most influencing variables among the missing data (PCA and HCA)
– Quantitative measurement of how much the outcome is affected by the use of an inappropriate LCI data set (MANOVA). The uncertainty measurements are realized on some specific step-related parameters: the geographical location of the step or the technology used at this step instead of measured input values (e.g., electricity consumption).

This paper is outlined in three sections.

First, the theory behind this work is detailed. We explain how, in practice, the LCA is very dependent on the relevance of the Life Cycle Inventory (LCI) data sets selected by the LCA practitioner. The representativeness of the LCI data set is indeed complemented by the appropriateness of the data set in the context of the specific system. The appropriateness characterizes in how far a data set in a system model represents the truly required process or product (European Commission 2010).

Then, the method developed to assess the appropriateness of an LCI data set at the system level is described.

Finally, the method is applied on textile manufacturing systems for which the diversity of processes is such that it is virtually impossible to model all possibilities (Boufateh et al. 2008). In the first subsection, the technical and geographical backgrounds of cotton harvesting, spinning, and weaving are described, and we explain how the LCI data sets were combined into systems. In the second subsection, the LCIA results for different geographical situations, for different technologies, and for different scenarios (average world scenario) at the spinning step are compared. They are analyzed in order to understand the origins of variations and identify the main influencing variables. In the third subsection, the errors associated with the use of inappropriate LCI data sets at each step of the manufacturing chain are assessed at two systems levels. The two systems levels considered are as follows:

– A manufacturing procedure combining two steps: cotton harvesting and yarn spinning
– A manufacturing procedure combining three steps: cotton harvesting, yarn spinning, and fabric weaving

2 Theory

The ability of the LCI data set to represent the environmental impacts of a system can be differentiated into two closely related aspects: representativeness and appropriateness. Note that in common LCA practice, both aspects are often covered by the term "representativeness."

- The first aspect, the representativeness, addresses how well the collected inventory data represents the "true" inventory of the process for which they are collected regarding technology, geography and time.

- The second aspect, the appropriateness refers to the degree to which a process data set that is used in the system model actually represents the "true" process of the analysed system. (European Commission 2010).

In system models, the data have to be both sufficiently representative and appropriate. There are hence the representativeness of a unit process data set inventory for the represented process and the appropriateness of an LCI data set for a required function on the system level. Combination of the two results in the overall representativeness of the LCI result inventory for the analyzed system; see Fig. 1.

Three notions must be distinguished to differentiate appropriateness from representativeness:

– The true process or inventory in the analyzed system

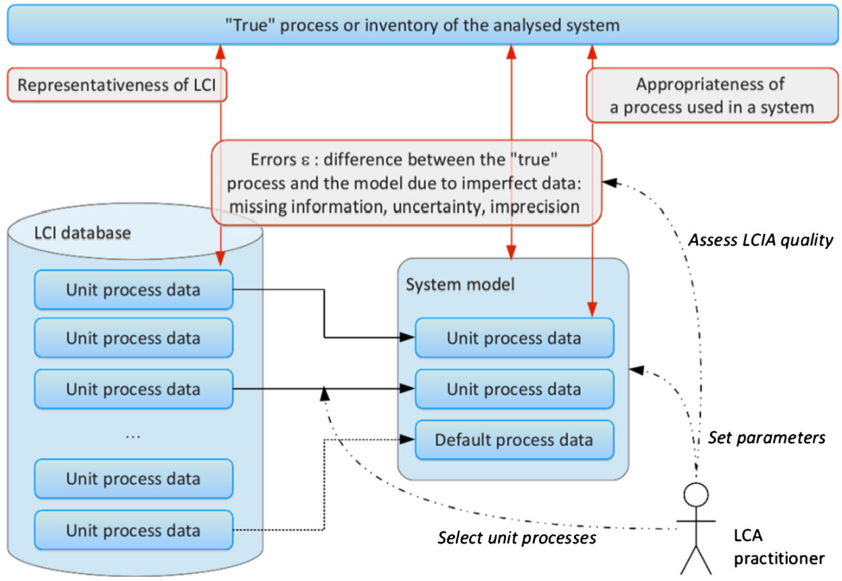

Fig. 1 Graph on representativeness and appropriateness

– The processes or inventories available in the LCI database
– The process or inventory selected by the LCA practitioner for a specific function in the analyzed system

Note that when the true process is not represented in the database, the errors ε cannot be calculated.

3 Methods

In the method proposed, the "true" process exists in the database. The database shall provide a geographical and technological overview of the supply chain studied or at least different LCI data sets representing the same process in different locations or with different technologies.

The errors measured are those resulting from a lack of information on the LCA practitioner side.

Appropriateness errors might come from the following:

– The choice of process variables
– The use of an inappropriate process
– The use of default models. When there is no information on a specific process, a common practice in LCA consists in representing the "true process" with a "default LCI data set."

The method proposed here to assess the percentage errors on appropriateness is the following:

- First, in order to account for uncertainty propagation in a linear chain of processes as recommended by Ciroth et al. (2004), different systems including the different versions of the LCI data sets are designed (see section 4.3).
- Second, some flow and impact indicators are selected as relevant illustrative variables (response variables), and the corresponding LCIA results are analyzed. The appropriateness errors are assessed on the LCIA results. The percentage errors resulting from the use of a default model are displayed in boxplots, giving an overall visual feedback of the quality of the model (from "very good" to "very poor"). A boxplot presents a dispersion of results through its five-number summaries: the smallest observation, lower quartile, median, upper quartile, and largest observation. Any data not included between the whiskers are plotted as an outlier with a small circle.
- Third, the input parameters contributing to variations in results are identified. Imbeault-Tétrault outlined the importance of identifying the input parameters contributing the most to output uncertainty, so the LCA analyst can take measures to reduce it (Imbeault-Tétreault et al. 2013). The two following analytical tools will provide information on the origins of the variations in LCIA results and will help in identifying the main influencing variables.

  – The hierarchical cluster analysis (HCA) is used to classify the data sets according to the similarity of their results. The R package pvclust is used to assess the uncertainty in hierarchical cluster analysis (Suzuki and Shimodaira 2006). Hierarchical clustering classifies data in clusters supported by p-values. The quantities called p-values are calculated via multiscale bootstrap resampling. Two types of p-values are presented: BP p-value (bootstrap probability), which is computed by normal bootstrap resampling, and AU p-value (approximately unbiased), which is computed by multiscale bootstrap resampling. The p-values of a cluster indicate how strongly

the cluster is supported by the data. The p-value of a cluster is a value between 0 and 1; clusters with p-values higher than 0.95 are strongly supported by the data. The HCA allows the identification of the most influencing variables and the grouping of processes with similar LCIA results. This tool is useful when the input variables are mostly unit process black boxes.

– The principal component analysis (PCA) is used to identify patterns in the data set LCIA results (Pearson 1901). It has the objectives of reducing the original variables into a lower number of orthogonal (non-correlated) synthesized variables (factors) eigenvectors. The PCA identifies patterns and helps the interpretation of results when the input variables are quantitative data. The PCA presents the advantage of accounting for possible correlations between inputs variables.

- Fourth, the results and the variables identified are jointly analyzed with the multivariate analysis of variances (MANOVA) to quantify the respective influences of the different input variables. MANOVA analyzes the variance–covariance between variables in testing the statistical significance of the mean differences of all illustrative variables (LCIA results). The MANOVA is mainly used for the evaluation of group variables and can account for the fact that there may be several correlated response variables. The MANOVA significance test is completed with the computation of the reduction of marginal variance (in percentage "explained") of each individual LCIA variable, when the default model uses a given set of input variables. This analytical tool is used to measure quantitatively the appropriateness of different variables. The MANOVA is used when the input variables are mostly unit process black boxes, in systems including more than two processes. MANOVA quantifies the influences of the main variables on the LCIA results.
- Finally, an appropriate default model can be developed with the PCA, HCA, and MANOVA conclusions.

4 Application to the textile industry

A review of the existing technologies and the geographical spread of the upstream processes in the textile manufacturing industry was carried out (see database content Electronic Supplementary Material). All the LCI data sets used in this study were developed as part of the EIME Textile LCI database development project (De Saxce 2012).

4.1 Technological background

Three textile manufacturing steps were studied: the harvesting of cotton fibers, the spinning of fibers into yarns, and the weaving of yarns into fabrics. The existing technologies were inventoried and represented at each step; see Table 1.

The different yarn spinning technologies are represented with five LCI data sets: thin combed, thin open-end, thick open-end, thin carded, and thick carded yarn spinning. Carded and open-end spinning use all fibers, when combing removes the short fibers so only long fibers are spun into yarns. Combed yarns are more resistant than carded yarns of the same thickness. The combing technology is used only for thin yarn manufacturing. To ensure a good technological representativeness of these LCI data sets, the following technology-related parameters were accounted for: the cotton input required, the use of the air conditioning, the lubricating of the fibers, the yarn torsion fixation, the yarn diameter, the waste generation, and the waste treatment (De Saxce et al. 2012).

The different weaving technologies are represented with five LCI data sets corresponding to five different looms (same number of pick per centimeter): projectile, air jet, conventional rapier, conventional shuttle, and "two-phase."

Table 1 Technologies represented for each manufacturing step

Manufacturing step	Cotton harvest (Kooistra et al. 2006)	Cotton yarn spinning (Laursen et al. 2007; Koç and Kaplan 2007)	Cotton weaving (Önder and Berkalp 2009)
Represented technologies	Conventional (99 %)	Thin carded (52 %)	Air jet
		Thin combed (27 %)	Two-phase
		Thin open end (18 %)	Shuttle
		Thick carded (75 %)	Rapier
		Thick open end (25 %)	Projectile
			Water jet
Default technology model		Thin yarn average	
Default technology model		Thick yarn average	

The surface mass of fabrics made with thin or thick yarns is different.

The "default LCI data sets" representing "average" spinning technologies were developed according to the following statistics:

– The "default thin yarn" consists in 52 % carded, 27 % open-end, and 18 % combed thin yarns.
– The "default thick yarn" consists in 75 % carded and 25 % open-end thick yarns (ITMF 2011; De Saxce et al. 2012).

4.2 Geographical background

The geographical spread of each process in the world was studied. The main manufacturing countries for each step are inventoried in Table 2.

To ensure the geographical representativeness of the cotton harvesting LCI, the following country specific factors were accounted for: yields, soil qualities, fertilizers, agricultural processes, pesticides, emissions to soil, groundwater, air, and surface water (Petit et al. 2013).

The development of the spinning and weaving LCI data sets in different geographical locations required the use of modular models as suggested by Ciroth et al. (2002). For these data sets, the following variables were country specific:

– Electricity production system (mix and efficiency)
– Heat production system (IEA 2010; Taylor et al. 2008)
– Water production system
– Waste treatment system

The "default LCI data sets," GLO and TOT, represent two world spinning averages. The GLO model represents a weighted average of the spinning processes located in the seven main producing countries. These seven countries accounted for almost 90 % of 2009 installed capacities (ITMF 2011). The TOT model represents a weighted average of the spinning processes located in the 15 main producing countries (eight more countries than in the GLO model). The total represented 98 % of world carded spinning in 2009. The completeness errors on the LCIA results generated by the use of GLO instead of TOT were assessed between −3 and 3.5 % on the indicators selected (De Saxce et al. 2012).

4.3 Combination of the LCI data sets into systems

To account for uncertainty propagation in a linear chain of processes as recommended by Ciroth et al. (2004), all the above LCI data sets were combined to represent manufacturing systems of two different levels.

The material transportations between the different steps were accounted for (cargo and lorry shipments).

These systems were designed to assess the appropriateness of the LCA practitioner choice of upstream processes at two different system levels; see Fig. 2. The choices are about the technology used or the geographical location of the upstream process on which there is no information.

First, 15 yarn manufacturing systems are compared, and the associated results are presented in section 5.2. Then, 605 fabric manufacturing systems are assessed, and their results are compared in section 5.3.

4.4 Flow and impact indicators selection

The assessment results were calculated only for midpoint impact categories. The following impact categories were selected among the recommended assessment methods by ILCD (2011):

– Climate change (GWP)
– Air acidification (AA)
– Water eutrophication (WE)
– Resource depletion (RMD)
– Ozone depletion potential (ODP)

The impact assessment models selected were not spatially differentiated to simplify the result analysis. However, the spatially differentiated impact assessment models would have

Table 2 Geographical locations represented for each manufacturing steps

Manufacturing step	Cotton harvest (Kooistra et al. 2006)	Cotton yarn spinning (ITMF 2011)	Cotton weaving (ITMF 2011)
Geographical distribution	China (32 %)	China (51 %)	China (63 %)
	India (24 %)	India (22 %)	Thailand (9 %)
	USA (13 %)	Pakistan (5 %)	Russia (7 %)
	Pakistan (11 %)	Indonesia (4 %)	Indonesia (6 %)
	Turkey (2 %)	Bangladesh (3 %)	Brazil (6 %)
		Turkey (3 %)	Turkey (5 %)
		Brazil (2 %)	Taiwan (3 %)
Global GLO default model		World average (90 % completeness)	
Total TOT default model		World average (98 % completeness)	

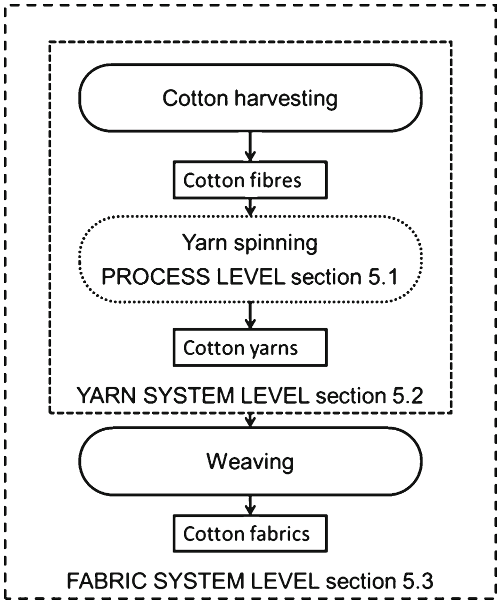

Fig. 2 Three levels of analysis

accounted for the geographical variability of specific elementary flow impact potentials (Huijbregts 1998; Owsianiak et al. 2013).

Two additional flow indicators were selected as control variable to check the consistency of results:

– ED: energy depletion indicator accounting for energy consumption either derived from the combustion of fuels (nuclear, fossils, or not) or from other sources (hydroelectricity, tidal, or solar).
– WD: water depletion indicator accounting for water consumption from any kind of water source or quality (drinkable, industrial, etc.).

5 Results and discussion

All the assessment results were obtained with the LCA software EIME (Bureau Veritas 2011). All statistical analyses were performed with R statistical software (R Development Core Team 2008).

Different situations were studied, where the LCA practitioner lacked information about the technology used or geographical location of the processes.

Section 5.1 focuses on the analyses of variations in LCIA results at the spinning process level. Similarly, Ciroth et al. (2002) assessed the technological and geographical variations on Life Cycle Inventories of waste incinerators. However, the tools applied in this paper account for possible correlations in the input variables.

Sections 5.2 and 5.3 are applications of the method to assess the appropriateness of an LCI data set at the system level.

5.1 Analyses at the spinning process level

The aim of this section is to study the respective influences of the spinning LCI data set input variables. The appropriateness of the “default average processes” presented in sections 4.1 and 4.2 is assessed.

The analytical tools applied are as follows:

– HCA to find out the origins of the variations in results
– PCA to visualize the correlations among the variables

5.1.1 Analysis of variations in LCIA results due to geographical changes

In this section, the variations in LCIA results induced by location changes are analyzed. Carded thin yarn spinning was modeled in seven countries and for two default models representing world averages: GLO and TOT. The LCIA results for these nine LCI data sets were compared and analyzed.

Figure 3 presents the dispersion of the LCIA results for each impact category.

Location changes for the “thin carded spinning” technology resulted in variations between −75.5 and 80 % on the indicators selected excluding the results on ODP. The ODP results showed high variation (−83/+709 %) because the selected assessment method associated high characterization factors with specific ozone-depleting substances.

As shown in Fig. 3, the variations due to a geographical change were significant.

We performed an HCA on the LCIA results to identify the main variables influencing the assessment results. Figure 4 presents a cluster dendrogram issued from the HCA performed. Values on the edges of the clustering are p-values (%). Left (red) and right (green) values are AU and BP p-values, respectively.

As shown in Fig. 4, China and the two default models were clustered together. The LCIA results of the default models (GLO and TOT) were very close to those of spinning in China (100 % AU p-value). Indeed, 57 % of yarn spinning in the world occurred in China in 2009 (ITMF 2011). The GLO and TOT default models were clearly not appropriate for the other countries.

China and India obtained close results. It is probably because both countries relied mainly on coal power plants for their electricity and heat production (IEA 2010).

The Brazil, Turkey, and Bangladesh processes were clustered separately from the others: Their LCIA results were lower than those of the other processes. It can be explained with the following statistics: Brazil relied mainly on hydroelectricity for its energy consumption, and Turkey and Bangladesh relied mainly on gas (IEA 2010). These electricity production systems were less polluting on the impact

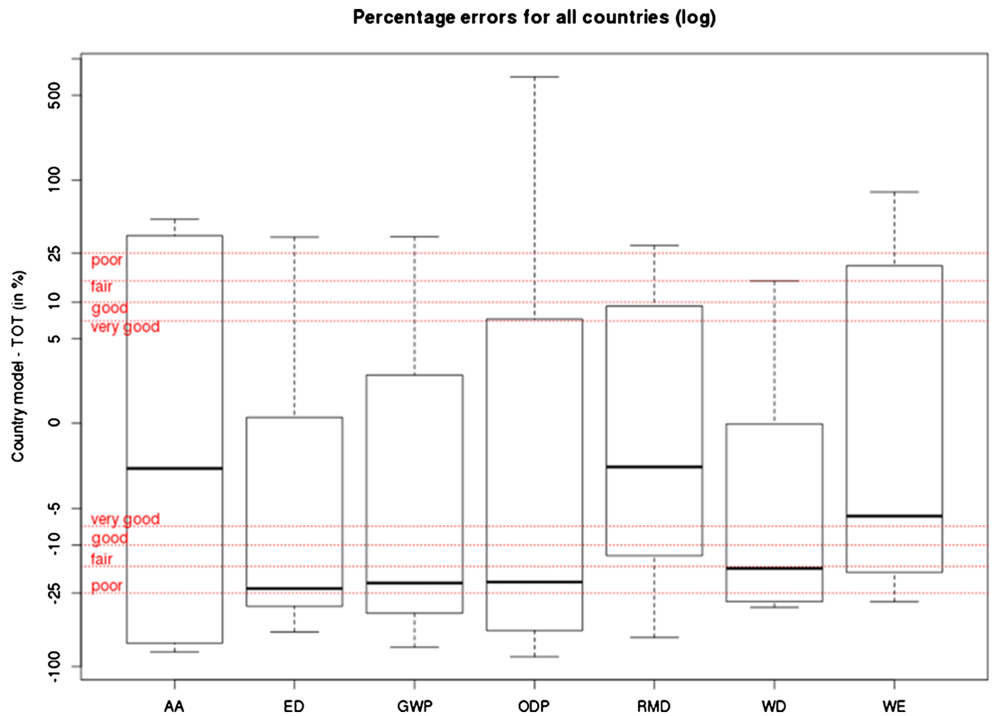

Fig. 3 Comparison of country models with the average model TOT for thin carded yarn spinning in the seven countries

categories selected. So, the country specific energy production system seemed to influence the results.

In fact, the geographical transfer of a process requires the replacement of "black box unit processes" included within, such as the country electricity mix. Thus, the access to raw data is limited, and because of this, the interpretation of the dispersion of the LCIA results resulting from location changes is difficult. In order to comprehend the complex relationship between the input data and the LCIA results, a deep technical knowledge and a complete traceability of the unit processes included within the LCI data sets are required.

We showed that performing an HCA allowed the following:

– The identification of the most influencing variables and
– The grouping of processes with similar LCIA results. It may guide the LCA practitioner through the selection of an appropriate process model by similarity in results.

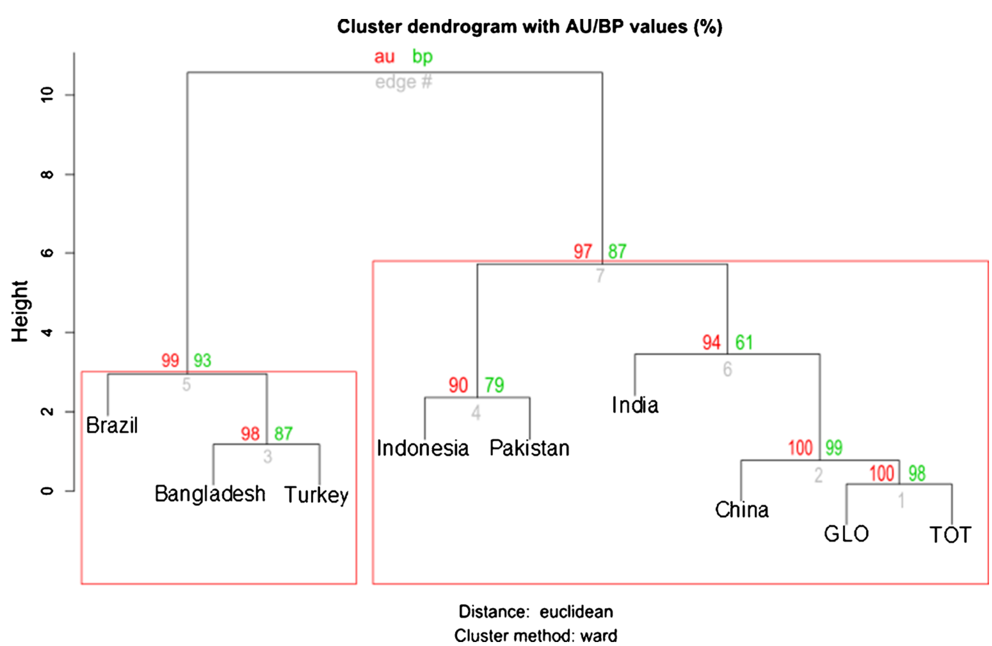

Fig. 4 Hierarchical cluster of the different processes according to their LCIA results

– The world average default models GLO and TOT were not appropriate to represent spinning in countries other than China.

5.1.2 Analysis of variations in LCIA results due to technology changes

This section aims at comparing the assessment results of different spinning technologies. The raw material production was accounted for because the yield varied for the different techniques. Seven yarn manufacturing processes all occurring in China were compared in this subsection.

The variations in results were included between −30 and 60 % depending on the impact categories selected. The LCIA results variations resulting from the use of the default models were between −20 and +20 %.

We performed two PCAs to visualize the correlations between the input variables and the assessment results.

In Fig. 5, the PCA biplot displays both the seven spinning technologies (dots) and the input variables: electricity consumption, cotton input, waste, and lubricant required quantities (vectors). Electricity appeared as an independent variable as opposed to the other three variables. The waste percentage, the lubricant, and the cotton input variables were closely related. This interdependence can be explained:

– The amount of lubricant needed was proportional to the amount of fibers introduced.
– The waste percentage determined the cotton input required.

The combed yarn manufacturing, represented in bright green, was the most energy and cotton consuming process. In combed spinning, a combing machine was added to the carded spinning process, so the electricity consumption increased. The percentage of cotton waste also increased because all the short fibers were removed. Consequently, a larger amount of cotton is required upstream for combed spinning.

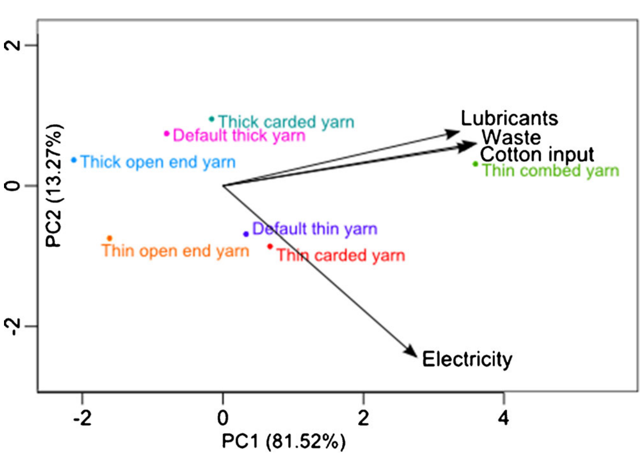

Fig. 5 Principal component analyses on input variables for the seven yarns in China

The open-end processes situated on the left side were less energy and cotton consuming.

The thick yarns were positioned above the thin yarns on the electricity vector. Manufacturing thick yarns was less energy consuming than manufacturing thin yarns because the spinning machines produced thick yarns at a greater speed than thin yarns.

In Fig. 6, the PCA biplot displays both the seven spinning processes and the seven impact and flow categories selected: WE, WE, ODP, AA, RMD, GWP, and ED (vectors).

The raw material depletion, the energy depletion, and the global warming potential vectors were oriented in close directions. Part of the energy (ED) was produced by combusting nonrenewable resources (RMD), and these combustions contribute to the global warming potential (GWP).

The combed yarn manufacturing process obtained higher results in all the impact categories. The combing electricity consumption explained the higher results on RMD, GWP, and ED. But the higher results on WE and WD categories were explained by the increased cotton input required. This increased cotton requirement resulted in higher water consumption and eutrophication at harvest.

On the other side, the open-end spinning technology was less impacting than the other technologies mainly because it generated less waste and consumed less energy.

Performing a PCA on input variables and interpreting the PCA on illustrative variables required a good technical knowledge of the process. This technique allowed the following:

– The identification of patterns in the LCIA results dispersion
– The understanding of the complex relationships between input variables and LCIA results
– The assessment of the appropriateness of the default models. The technological appropriateness errors resulting from the use of the “default thick yarn” or the “default thin yarn” were between −20 and +20 %.

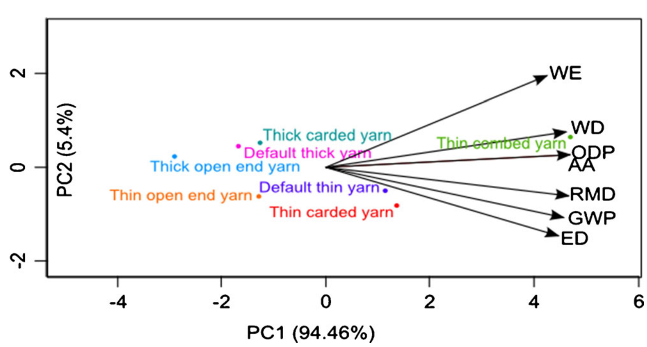

Fig. 6 Principal component analysis on LCIA results for the seven yarn manufacturing processes in China

5.2 Multi-analysis of variables at the yarn system level

To assess the technological appropriateness of a spinning process (default or technology specific), yarn manufacturing systems were designed combining cotton harvest and cotton spinning LCI data sets. In order to account for only one location variable, cotton harvest and yarn spinning were located in the same country. A total of 15 yarn manufacturing systems located in China, India, and Turkey were studied: five in each country.

The aim was to estimate the best default model assuming that the spinning technology was unknown. To assess the significance of each variable on the results, we performed an HCA on the LCIA results obtained for each yarn.

In the cluster dendrogram presented in Fig. 7, the clusters either set together: technologies in the same location or technologies aiming at the same yarn thickness (see red rectangles, with AU p-value of more than 91 %). So, we identified the geographical location and the yarn thickness as the two main variables influencing the LCIA results.

To assess and quantify the respective influences of these variables, we performed a MANOVA analysis on the LCIA results, concluding to their high significance (Pillai–Bartlett test). The following three variables altogether were sufficient to explain the variance of the LCIA results for the yarn manufacturing processes:

- The spinning technology that was used
- The harvesting and yarn spinning location
- The yarn thickness obtained

Table 3 presents the percentage marginal variance explained by each single input variable on each impact category. As shown in Table 3, the percentage marginal variance explained by the variable *location* was between 85 and 92 % except for ED and GWP results. The percentage marginal variance explained by the spinning technology was below 15 % except for the ED and GWP results, which are, respectively, 27 and 55 %. The percentage marginal variance explained by the yarn thickness was below 7.1 % except for ED and GWP results, which are, respectively, 24 and 48 %. The geographical location was the most influencing input variable.

As shown on Fig. 8, setting the two variables yarn thickness and geographical location improved ED and GWP to 70 % variance explained. The technological appropriateness errors resulting from the use of this default model were between −18 and +17 %.

The "default thin or thick yarns" weighted by the quantities produced and computed per country and per yarn thickness (described in section 4.1 and assessed for China in section 5.1.2) were not very different from this default model: Variations were within +/−3 %.

Overall, we showed that

- The yarn thickness needed to be accounted for in a default model for yarn manufacturing. The yarn thickness could be retrieved from the manufactured product.
- The "default yarn models" should be country specific to avoid high appropriateness errors.

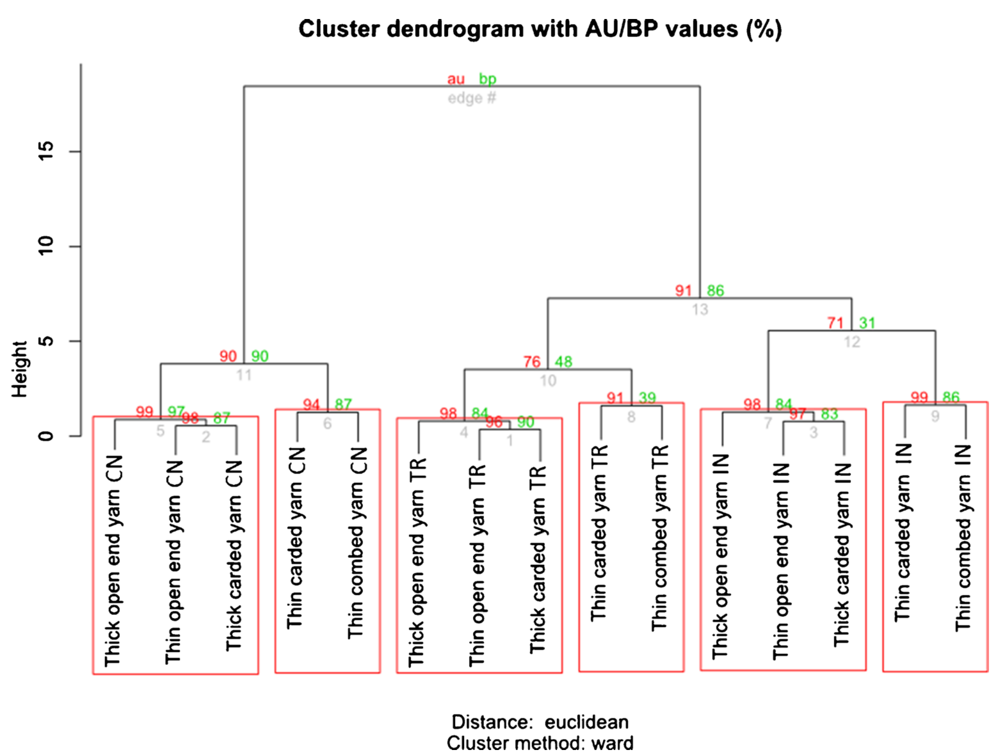

Fig. 7 Cluster analysis of the LCIA results for the 15 yarn manufacturing systems located in China (*CN*), Turkey (*TR*), India (*IN*)

Table 3 LCIA results of yarn manufacturing processes with percentage marginal variance explained for each input variable

Input variables	AA (%)	ED (%)	GWP (%)	ODP (%)	RMD (%)	WD (%)	WE (%)
Yarn thickness	3.5	25	49	6.3	7.1	3.2	2.3
Spinning technology	5.0	28	55	11	14	13	15
Geographical location	92	59	19	85	83	86	84

5.3 Multi-analysis of variables at the cotton fabric system level

The respective influences of a wrong technological or geographical choice on the LCIA results can be less important for some processes than for others. In this section, 605 fabric manufacturing systems were compared to assess the relative geographical or technological appropriateness errors related to each manufacturing step.

The input variables were as follows:

- The cotton harvest location
- The spinning location
- The weaving location
- The spinning technology
- The weaving technology

To study the respective influences of these variables, we performed a MANOVA analysis on the LCIA results. Table 4 presents the percentage marginal variance explained by each input variable on each LCIA.

In Table 4, the results on WD and WE were mostly explained by the cotton harvest location. The cotton harvest location explained 96 % of the variance on the water eutrophication results and 91 % of the results on water depletion. The fertilizer requirements and their corresponding lixiviation were country specific which explains the results. The weaving and spinning technologies explained 30 % of the marginal variance on GWP results and 28 % on ED.

The influence of the "harvesting location" on the LCIA results (particularly on the eutrophication potential and water depletion) was mainly significant compared to the locations and technologies of the other manufacturing processes.

Figure 9 presents the percentage variance explained by a regression model with the following three-variable set: harvest, spinning, and weaving locations.

Figure 9 shows that the combination of the three locations was highly significant and explained most of the results since the percentages of marginal variance explained were all above 68 % with this model. With the three location variables set in the default model, 72 % of the 605 samples were "fairly"

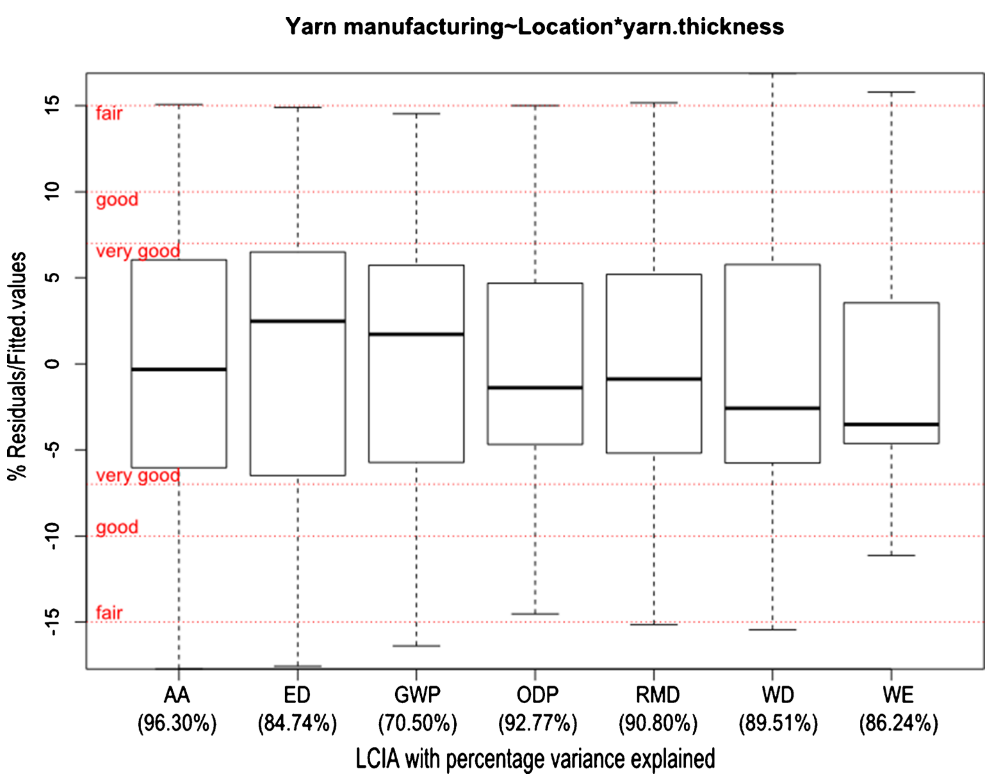

Fig. 8 Yarn manufacturing processes, percentage errors, and percentage marginal variance explained by a regression model with two variables (location and yarn thickness)

Table 4 LCIA results of cotton fabrics with percentage marginal variance explained for each input variable

Input variables	AA (%)	ED (%)	GWP (%)	ODP (%)	RMD (%)	WD (%)	WE (%)
Cotton harvest location	70	53	34	2.1	84	91	96
Spinning location	10	10	17	63	2.8	0.74	0.036
Weaving location	8.7	7.8	15	32	4.7	0.70	0.00
Spinning technology	7.1	17	20	11	6.9	6.8	3.4
Weaving technology	1.5	11	9.2	4.6	3.4	0.2	0.00
Two technology variables	8.7	28	30	15	10	7.0	3.4

modeled (less than 15 % error) with the default model, and 91 % of the cotton fabrics had less than 25 % errors.

The use of a default fabric manufacturing model, in which the three yarn manufacturing locations were set, resulted in –20 %/+20 % variations in LCIA results. The error left was due to the technological inappropriateness of the model.

6 Conclusions

When it comes to missing data, a large variety of parameters introducing uncertainties in the results exist from "an input flow quantity" (e.g., "electricity consumption for an upstream process") to "the location of an upstream process." This is why assessing the appropriateness of an LCI data set on a system level necessitated a new approach and specific analytical tools.

The appropriateness assessment method presented in this paper comprises several steps including the identification of the main influencing variables and the uncertainty assessment.

Once the steps that are difficult to track in the textile supply chain were identified, e.g., upstream processes, the appropriateness assessments were conducted in the following way:

– The influences of a lack of information on each step were assessed. The HCA tool has proven effective in identifying the main variables influencing the LCIA results. The appropriateness errors associated with the use of the "default world average models" were too high. The PCA has proven helpful to understand the complex relations between the input variables and the LCIA results.
– In the two case studies, the MANOVA performed identified *the locations* as the main variables influencing the results. In such cases, the geographical transfer of LCI

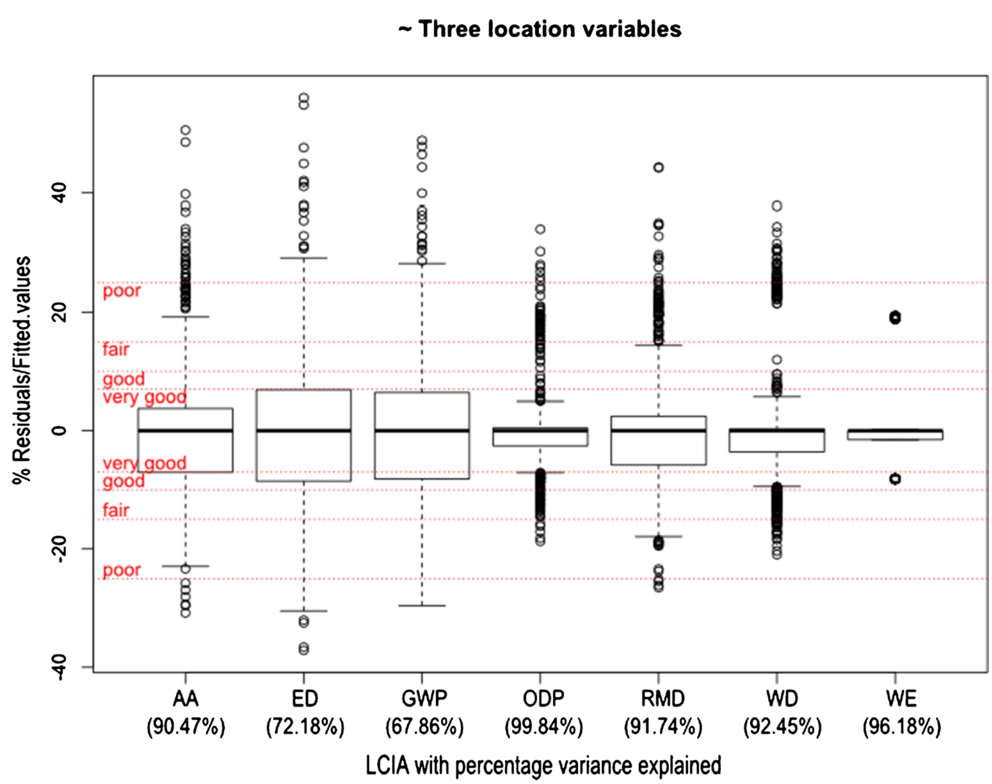

Fig. 9 Cotton fabrics, percentage errors, and percentage variance explained by a regression model with three variables (harvest, spinning, and weaving locations)

data sets should be preferred over the use of "default world average LCI data set."

– The MANOVA results enabled the development of two appropriate default models to account for missing data on technological aspects. The appropriate default processes were developed by setting the parameters with a significant influence on the results.

Thus, we demonstrated that performing an appropriateness assessment can prevent the use of inappropriate default geographical or technological aggregations. The appropriateness assessment has proven effective in assisting the LCA practitioner in the modeling of textile manufacturing systems.

This method can easily be applied on other worldwide multi-step manufacturing systems and will thus increase the understanding of such systems.

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References

Benetto E, Dujet C, Rousseaux P (2008) Integrating fuzzy multicriteria analysis and uncertainty evaluation in life cycle assessment. Environ Model Softw 23(12):1461–1467

Bojaca CR, Schrevens E (2010) Parameter uncertainty in LCA: stochastic sampling under correlation. Int J Life Cycle Assess 15(3):238–246

Boufateh I et al. (2008) Life Cycle Assessment: data availability, reliability and robustness in textile industry. 8th AUTEX Conference-Working towards change: Academy and Industry together, Biella (Italy), 24 – 26 June (CD-Rom version); 2008. In 8th AUTEX Conference- Working towards change: Academy and Industry together, 24 – 26 June. Biella, Italy

Bureau Veritas CODDE (2011) EIME, Environmental Improvement Made Easy v.5. Available at: https://demo.bveime.com

Chevalier J-L, Téno J-FL (1996) Life cycle analysis with ill-defined data and its application to building products. Int J Life Cycle Assess 1(2): 90–96

Ciroth A et al (2002) Geographical and technological differences in Life Cycle Inventories shown by the use of process models for waste incinerators. Part I. Technological and geographical differences. Int J Life Cycle Assess 7(5):295–300

Ciroth A, Fleischer G, Steinbach J (2004) Uncertainty calculation in life cycle assessments – a combined model of simulation and approximation. Int J Life Cycle Assess 9(4):216–226

De Saxce M (2012) Méthodologie pour l'évaluation des impacts environnementaux des textiles par l'Analyse du Cycle de Vie. Manuscrit de thèse. Université de Lille Nord de France, GEMTEX laboratory

De Saxce M, Rabenasolo B, Perwuelz A (2012) Technological, geographical uncertainty measurements for textile spinning processes. In: 6th International SETAC congress. Berlin

European Commission (2010) ILCD handbook - General guide for life cycle assessment - Detailed guidance, Directorate General Joint Research Centre

Heijungs R, Suh S, Kleijn R (2005) Numerical approaches to life cycle interpretation – the case of the Ecoinvent'96 database. Int J Life Cycle Assess 10(2):103–112

Huijbregts MAJ (1998) Application of uncertainty and variability in LCA. Part I: a general framework for the analysis of uncertainty and variability in life cycle assessment. Int J Life Cycle Assess 3(5): 273–280

IEA and OECD (2010) International Energy Agency database. Statistics and balance per country. Available at: http://www.iea.org/stats/index.asp

ILCD (2011) ILCD handbook - Recommendations for Life Cycle Impact Assessment in the European context production. JRC, ies

Imbeault-Tétreault H et al (2013) Analytical propagation of uncertainty in life cycle assessment using matrix formulation. J Ind Ecol 17(4): 485–492

ITMF (2011) International textile machinery shipments statistics, International Textile Manufacturers Federation, Zürich, Switzerland

Koç E, Kaplan E (2007) An investigation on energy consumption in yarn production with special reference to ring spinning. Fibres Text East Eur 15(4):18–25

Kooistra K, Termorshuizen A, Pyburn R (2006) The sustainability of cotton consequences for man and environment, Science Shop Wageningen UR, report 223. Wageningen University, The Netherlands

Laursen SE et al. (2007) EDIPTEX – Environmental assessment of textiles, Working report n°24, Danish Ministry of the environment, Environmental protection Agency

Lloyd SM, Ries R (2008) Characterizing, propagating, and analyzing uncertainty in life-cycle assessment: a survey of quantitative approaches. J Ind Ecol 11(1):161–179

Maurice B et al (2000) Uncertainty analysis in life cycle inventory. Application to the production of electricity with French coal power plants. J Cleaner Prod 8(2):95–108

May JR, Brennan DJ (2003) Application of data quality assessment methods to an LCA of electricity generation. Int J Life Cycle Assess 8(4):215–225

Önder E, Berkalp ÖB (2009) Weaving technology: weft insertion rate of different looms. Istanbul Technical University, Department of Textile Engineering

Owsianiak M et al (2013) Addressing geographic variability in the comparative toxicity potential of copper and nickel in soils. Environ Sci Technol 47(7):3241–3250

Pearson K (1901) LIII. On lines and planes of closest fit to systems of points in space. Philos Mag 2(11):559–572

Petit J, Lanfranconi A, Gimat C (2013) Présentation d'une méthodologie de calcul des émissions au champ dans le cadre de la simplification des ACV en agroalimentaire. In: Symposium EcoTechs. Bureau Veritas CODDE presentation. Vitry

R Development Core Team (2008) R - a language and environment for statistical computing. Available at: http://www.r-project.org

Sonnemann GW, Schuhmacher M, Castells F (2003) Uncertainty assessment by a Monte Carlo simulation in a life cycle inventory of electricity produced by a waste incinerator. J Clean Prod 11(3): 279–292

Suzuki R, Shimodaira H (2006) Pvclust: an R package for assessing the uncertainty in hierarchical clustering. Bioinformatics 22(12):1540–1542

Taylor P et al (2008) Energy efficiency indicators for public electricity production from fossil fuels: An International Energy Agency (IEA) Information Paper in Support of the Group of Eight (G8) Plan of Action

Weidema BP, Wesnaes MS (1996) Data quality management for life cycle inventories – an example of using data quality indicators. J Clean Prod 4(3):167–174